A Prediction Market for Macro-Economic Variables

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Abstract

Macro-economic forecasts are used extensively in industry and government even though the historical accuracy and reliability is disputed. Prediction markets have proven to successfully forecast the outcome of elections, sport events and product sales. In this paper we provide a detailed analysis of forecasts generated from a new prediction market for economic derivatives. The proposed market design is specifically designed to forecast macro-economic variables and differs significantly from previous ones. It solves some of the known problems such as low liquidity and partition-dependence framing effects. By using finance methodology we firstly show that the market is reasonably liquid in order to continuously generate forecasts. Secondly the market forecasts performed well in comparison to the 'Bloomberg'- survey forecasts. Thirdly forecasts generated by the market fulfill the weak-form forecast efficiency implying that forecasts contained all publicly available information.

1. Introduction

A wide and important range of policy decisions are made on the informational basis of economic forecasts such as GDP growth. It is a well established fact that traditional economic forecast models lack the necessary accuracy [25], [23], [26]. Simplified, the current approaches mix expert knowledge with historic extrapolation. They are thus inadequate to capture rapid economic changes, as exemplified in the 2008 recession. Yet another issue is the reliance of the current forecasts on expert input. Experts are prone to biases and political influence and generally do not perform better than novices in forecasting future events [2]. Prediction markets have a long track of successful application in a wide area ranging from political to sport events sometimes outperforming established forecast methods [5], [19]. We thus setup a prediction market for economic variables called Economic Indicator Exchange (EIX). The EIX *play money* prediction market is specifically designed to forecast economic indicators such as GDP, inflation,

investments, export and unemployment figures in Germany. By comparing the market forecasts to 'Bloomberg'-survey forecasts we show the potential of markets as information aggregation tools.

The remainder of this paper is structured as follows: the second section gives a brief review of previous markets for economic variables and discusses possible shortcomings. The third section develops the new market design and details the field experiment setting. Section four presents the evaluation methodology. The fifth section first analyzes the market from a finance perspective and then from a forecasting perspective. Finally section six concludes this paper.

2. Related work

Prediction markets have proved to successfully forecast events in a wide range of applications. They facilitate and support decision making through aggregating expectations about events [17]. The roots of their predictive power are twofold; the market provides the incentives for traders to truthfully disclose their information and an algorithm to weight opinions [3]. The most basic trading mechanism for prediction markets is based on a continuous double auction for one stock which represents the outcome of an event. The stock will pay 1 if an event has the predicted outcome, otherwise the stock will be worthless. Market participants hold beliefs about the likelihood of an event. Comparable to financial markets, they buy if they find that prices underestimate the event in question and participants sell a stock if they find that prices overestimate the probability of an event. One famous example is the Iowa political stock market (PSM) which tries to predict the outcome of U.S. presidential elections. The Iowa PSM features contracts that represent one nominee each. Market participants buy and sell nominee contracts depending on their assessment of the U.S. presidential election outcome. The U.S. presidential elections are well suited for a prediction market as in the final pre-

election period only two candidates have a chance of winning the election which gives the market two complementary assets. Also, only one of the nominees will win and the other one will lose. The first stock pays 1 if the second is stated at 0 and vice versa. Which means a stock pays 1 if the corresponding nominee wins an election. Usually this market design offers the possibility to buy and sell bundles of both stocks for 1 [4] which imply that in a frictionless world with rational traders both stock prices always sum up to 1. The above described form of representing a single event with two complementary stocks has been the norm since its proposal. In fact the concept has been so successful that it was adapted for events with more than two outcomes. For example, Luckner and Weinhardt [20] design a market to predict the outcome of the soccer world cup where the value of all 32 stocks combined is predefined. All traded stock prices are dependent as there is by definition only one world champion.

2.1. Markets for economic derivatives

Markets for macro-economic variables have been used since the 80s. The Coffee, Sugar and Cocoa Exchange established a futures market on the consumer price index allowing traders to hedge on inflation. The market was, however, closed due to low interest [22]. In 1993 Robert Shiller [28] argued for the creation 'Macro Markets' which would allow a more effective risk allocation. In 2002 Goldman Sachs and Deutsche Bank set up the so called 'Economic Derivatives' market tied to macro-economic outcomes such as ISM Manufacturing, change in Non-Farm Payrolls, Initial Jobless Claims and consumer price index [14]. The traded contracts are securities where payoffs are based on macroeconomic data releases. The instruments are traded as a series (10-20) of binary options. For example a single data release of the retail sales in April 2005 was traded as 18 stocks. In order to maximize liquidity the market operators used a series of occasional Dutch Auctions just before the data releases instead of the more common continuous trading on most financial markets. Thus the market provided hedging opportunities against event risks and a short horizon market forecast of certain economic variables. By analyzing the forecast efficiency Gurkaynak and Wolfers [16] find that market generated forecasts are very similar but more accurate than survey based forecasts (One must note that the Bloomberg survey forecasts are published on Fridays before the data release, whereas the auction was run -and the forecast was generated- on the data release day.)

In an attempt to forecast inflation changes in Germany, Berlemann and Nelson [7] set up a series of

markets. The markets feature continuous trading of binary contracts. In a similar field experiment Berlemann et al. [6] used a similar system in order to aggregate information about inflation expectations in Bulgaria. All in all, the reported forecasts results in both experiments are mixed and not too promising. Besides the low number of forecast events both experiments suffer from low public interest resulting in illiquid markets.

2.2. A Case for a new market design

As detailed in the last section, the previous research focused on binary contracts. However, the standard approach reaches its limits if the number of outcomes is very high or even infinite. For instance, in a market to assess GDP growth, possible outcomes range from -100% to infinity. A common work-around is to set arbitrary intervals over the range of possible outcomes and trade each interval as an individual stock. The market operator faces two decisions in such a setting. First, they have to pre-estimate a reasonable range of possible outcomes. Second, they have to set corresponding intervals. E.g. if the pre-estimated window for GDP growth is between 0% and 5% then the market operator still needs to define the number of intervals. A fixed interval size already limits the accuracy of the prediction and the choice of range might bias a prediction market's results. In the GDP case mentioned, market participants have the choice of six answers (six different stocks) in 1% intervals. Even if market participants predicted the right interval, such a prediction market would still yield inaccurate forecasts. Additionally as it is desirable to forecast not only the next upcoming period but longer horizons, the number of needed contracts rises. Using binary contracts with 1 %-intervals, five indicators and three periods per indicator would lead to a minimum of 60 contracts. The high number of contracts would result in low liquidity and eventually diminish the forecast accuracy [9], [1].

Furthermore, Sonnemann et al. [29] indicate on the dataset of the 'Economic Derivatives' market a bias called 'partition-dependence'. They show that by arbitrarily setting intervals on the state space the market operator influences the judged likelihood. Thus all previous markets suffer from a bias induced by the market operator. On one hand it seems unintuitive to represent more or less continuous outcomes through intervals; on the other hand theory predicts that traders would arbitrage away the inefficiencies. The benefit of representing an event with contrary stocks is out-leveraged by the hassle of trading a large number of stocks. The market design -proposed in this paper- tries

to circumvent the laid out problems by representing events as linearly paid out contracts.

3. Field experiment

In October 2009 a play money prediction market was launched specifically designed to forecast economic indicators such as GDP, inflation, investments, export and unemployment figures in Germany. The goal is to forecast the indicators over longer time periods in advance and continuously aggregate economic information. The market called Economic Indicator Exchange (www.eix-market.de) was launched in cooperation with the leading German economic newspaper 'Handelsblatt'. The cooperation aims at reaching a wide and well informed audience interested in financial markets and economic development. We thus expect no problems understanding the indicators and the concept of trading. The market is publicly available over the Internet and readers where invited to join. The registration is free and requires besides a valid email address just minimal personal information.

3.1. Market design

The market design features a continuous double auction (CDA) without a designated market maker. Participants are allowed to submit marketable limit orders with 0.01 increments through the web-based interface.

The trading interface is displayed in Figure 1. Participants have convenient access to the order book with 10 levels of visible depth (1), the price development (2), the account information (3) and market information such as the last trading day (4). As additional information the Handelsblatt provides access to an up-to-date economic news-stream (5) and finally the indicators last year's performance (6) are displayed. Participants are able to customize their trading interface individually. By clicking the small arrows the six information panels open and close. In the default setting, only the trading mask and the six headlines are visible. After registration participants are endowed with 1,000 stocks of every contract and 100,000 play money units.

3.2. Contracts

The contracts are designed to circumvent the problems of liquidity and market operator induces bias described in the previous section. We propose to represent continuous outcomes with one stock and define a linear payout function. Contracts for each economic indicator are paid out according to equation 1.

$$p = 100 + \alpha \times \left(\frac{I_{t0} - I_{t-1}}{I_{t0}} \right) \ with \ \alpha = 10 \qquad (1)$$

A contract is worth: 100 +/- α times the percentage change for an indicator in play money. We set α to 10. (e.g. a change of 2.1 % results in a price of 121) Therefore, the representable outcome ranges from -10% to infinity. In order to represent the whole outcome range from -100% to infinity, α could be set to one. Previous work indicates that market participants find it difficult to estimate minor changes in the underlying [30]. Hence we propose to scale the minor changes to a certain level. Looking at historical
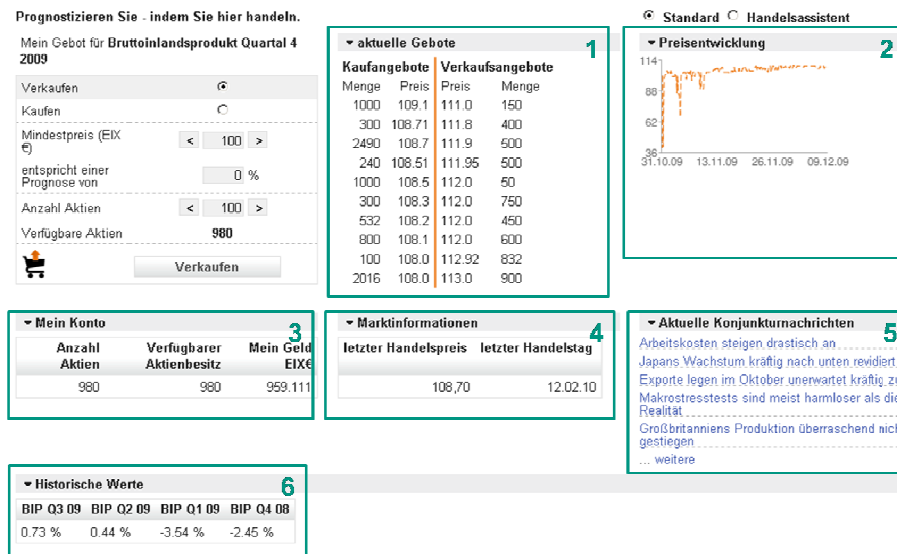

Figure 1: Trading screen with open information panels

data there were no events where German GDP dropped 10% per quarter. The rationale for setting α to 10 was the deliberation that participants find it more intuitive to enter integers in order to express reasonable accuracy. Additionally German statistical data releases rarely come with more than one decimal.

Indicator	Unit	Release cycle	# Payouts
Exports	%-Changes (t-1)	monthly	4
GDP	%-Changes (t-1)	quarterly	2
Inflation	%-Changes (t-12)	monthly	5
Investments	%-Changes (t-1)	quarterly	1
Unemployment	Million(abs)	monthly	5

Table 1: Economic variables

Table 1 summarizes the economic variables tradable on the market. Due to the payout function and the selection of the corresponding units; all stock prices are expected to roughly range between 50 and 150. Therefore participants could similarly gain by investing in specific indicators. The indicators are a mix of leading (e.g. Investments) and lagging (e.g. Unemployment numbers) economic indicators.
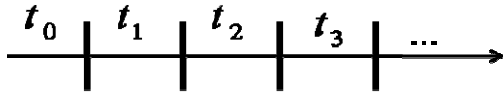

Figure 2: Timeline, multiple contracts

To facilitate longer forecast horizons every indicator is represented by three independent stocks each representing the next three data releases (t_1, t_2, t_3 see Figure 2). As a consequence the initial forecast periods vary from 1 month for monthly released indicators up to 3 quarters for quarterly released variables. One day before the release date the trading in the concerned stock is stopped. Finally the stocks are liquidated according to the payout function defined in equation 1. As soon as the trading in one stock stops a new stock of the same indicator (e.g. t_4) is introduced into the market. This means that participants received 1,000 new stocks of the respective indicator. All in all participants are able to continuously trade 15 stocks at all times.

3.3. Incentives

As previously mentioned, the market is a free to join play money market. In order to motivate participants intrinsically we provided two interface features; traders could follow their performance on a leader board and they could form groups with others to spur competition with friends. Previous research in the field of prediction markets has shown that play-money markets perform equally well as real-money markets at predicting future events [27],[32]. Note also that due to legal restrictions on gambling the EIX prediction market has to rely on play money.

To increase participants' motivation and to provide incentives to truly reveal information we hand out prizes worth 36,000 Euro. In order to be useful, an accurate prediction must be determined well in advance of the actual outcome. It makes little sense to run a market where one obtains the prediction just before the actual outcome occurs. This sounds obvious, but it is actually quite difficult to achieve, because traders want to know how their 'investment' turned out, fairly quickly. As we try to forecast longer periods the incentive scheme has to address this problem. So the incentives are divided in two parts (a) monthly prizes and (b) yearly prizes. The 8 yearly prizes (total value 10,000 Euro) are handed out according to the portfolio ranking at the end of the market. The monthly prizes are shuffled among participants who fulfilled two requirements for the respected month: (i) they increased their portfolio value and (ii) they actively participated by submitting at least five orders. Both incentives are clearly communicated through the interface. For the yearly prizes the leader board indicates the current status of all participants. The monthly winning status is displayed individually just after each login.

4. Methodology

In the following section we detail the tools to systematically analyze the market. As it is rather untypical to report market measures in the prediction market community; we rely on financial market literature (To our knowledge, there is no paper in this research area reporting liquidity measures). As we cannot directly compare the market designs in a field experiment we use market and forecast efficiency as a proxy. First several liquidity and error measures are presented followed by a model to measure forecast efficiency.

4.1. Liquidity measures

Liquidity represents the transaction cost market participants face to trade. A measure for the liquidity is an asset's ability to be sold rapidly, with minimal loss of value, any time within market hours [18]. We calculate half-spreads rather than round-trip (full)

spreads. Quoted spreads are the simplest and most common measure of trading costs and can easily be calculated using trade and order book data. All calculations presented below are spreads relative to stock price and are reported in basis points (bps). Let $Ask_{i,t}$ be the ask price for a $stock_i$ at time t and $Bid_{i,t}$ the respective bid price. $Mid_{i,t}$ denotes the mid quote then the quoted spread is calculated as follows:

$$Quoted\ Spread_{i,t} = \frac{(Ask_{i,t} - Bid_{i,t})}{2 * Mid_{i,t}} \qquad (2)$$

Additionally we separate in quoted spread and quoted spread at trade, the first measure includes all order book changes whereas the second is limited to quotes just before a trade is executed. The effective spread is the spread paid when an incoming market orders trades against a limit order. Since quoted spreads at trade only measure the trading costs for the smallest of trade sizes, a more accurate measure of execution costs are given with the effective spreads. Let $Price_{i,t}$ be the execution price then the effective spread is defined as:

$$Effective\ Spread_{i,t} = D_{i,t} * \frac{(Price_{i,t} - Mid_{i,t})}{Mid_{i,t}} \qquad (3)$$

$D_{i,t}$ denotes the trade direction, -1 for a sell and +1 for a buy order. The realized spread measures liquidity supplier revenues independent of the adverse selection costs imposed on the uninformed by the informed [8]. The Glosten-Milgrom model [15] also highlights that spreads widen if the risk of trading against asymmetrically informed traders is high in order to compensate for losses to such traders. The realized spread is calculated with the mid-quote (x) minutes/hours after the trade as follows:

$$Realized\ Spread_{i,t} = D_{i,t} * \frac{(Price_{i,t} - Mid_{i,t+x})}{Mid_{i,t}} \qquad (4)$$

4.2. Information measures

Price impact is an approximate measure of the adverse selection component of the effective spread. The price impact is the effective spread minus the realized spread and measures the information content of a trade. It approximates the permanent impact of a trade under the assumption that information impacts are permanent and realized at the x-minute mark. Following a trade, liquidity suppliers adjust their beliefs about the fundamental value of an asset depending on the information content of a trade (cf. [15]). The simple price impact of a trade is calculated as follows:

$$Price\ Impact_{i,t} = D_{i,t} * \frac{(Mid_{i,t+x} - Mid_{i,t})}{Mid_{i,t}} \qquad (5)$$

The price impact provides an indication of the information content of a trade.

In binary markets the prediction markets prices typically provide useful (albeit sometimes biased) estimates of average beliefs about the probability an event [21], [33]. In our linear outcome market, prices do not reflect the probability of an outcome but the market participant's aggregated belief about the fundamental value of the underlying indicator. Thus the interpretation of the price is directly linked to the outcome value. In our case there are various ways to generate an economic forecast from market prices. For example participants can either infer that the $Mid_{i,t}$ or the last trading price are the forecast for $stock_i$ at time t. In the following sections a $market\ forecast_t$ refers to the average transaction price on day t.

The probability of informed trading (PIN) represents the implicit risk that a market participant faces when trading with a better informed participant on the direction of the underlying event.

By following Easley et al. [10] we calculate PIN as depicted in equation 6:

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_s + \varepsilon_b} \qquad (6)$$

In the model $\alpha\mu + \varepsilon_s + \varepsilon_b$ gives the arrival rate for all orders, and $\alpha\mu$ is the arrival rate for information based orders. In effect the model interprets the normal level of buys and sells per day in a stock as uninformed trade and it uses this data to identify $(\varepsilon_s, \varepsilon_b)$. The days with abnormal levels of buys and sells are interpreted as information-based trading and used to identify α. In order to estimate the model, one only needs the number of buyer- and seller-initiated trades.

4.3. Error measures

A first indication about the market outcome is given by the deviation between market prices and fundamental values. In the following sections the difference between the fundamental value of the $stock_i$ and the $market\ forecast_{t,i}$ represents the $error_{t,i}$. One would expect market prices to converge to the final outcome and thus a reduction of forecast error over time.

Measure	Definition
Mean Absolute Error (MAE_t)	$\frac{\sum_{i=1}^{n} Error_{i,t}}{n}$
Mean Absolute Percentage Error ($MAPE_t$)	$\frac{\sum_{i=1}^{n} \frac{Error_{i,t}}{fv_i}}{n}$
Percent Mean Absolute Deviation ($PMAD_t$)	$\frac{\sum_{i=1}^{n} Error_{i,t}}{fv_i}$
Mean Squared Error (MSE_t)	$\frac{\sum_{i=1}^{n} Error_{i,t}^2}{n}$
Root Mean Squared Error ($RMSE_t$)	$\frac{\sum_{i=1}^{n} \sqrt{Error_{i,t}^2}}{n}$

Table 2: Error measures

In order to exhibit the error reduction we will use the measures presented in Table 2. A detailed discussion of the presented measures can be found in [13].

4.4. Forecast efficiency

This section adapts a test by Nordhaus [24] on weak form forecast efficiency in which the forecasts contain all information at the time of the forecast. This means that all forecast revisions and errors should be uncorrelated with past forecast revisions. Expressed differently, revisions and errors should follow a random walk. In the following equations a revision is defined as:

$$revision_{i,t} = forecast_{i,t-1} - forecast_{i,t} \qquad (6)$$

To test for correlation we use the following OLS regression:

$$rev_{i,t} = \alpha * rev_{i,t-1} + \beta * rev_{i,t-2} + \gamma * rev_{i,t-3} \qquad (7)$$

The regressions are estimated with robust standard errors [30]. The methodology follows [7] and [16].
Note that forecast efficiency differs from market efficiency by Fama [11], [12]. On a technical level we do not test for correlation (a random walk) on a trade by trade basis but on an aggregated daily level. We first construct forecasts from market prices –not based on single transactions- and measure if these forecasts reflect all previous forecasts. In contrast to that, tests on market efficiency determine if every transaction reflects all previous public information.

5. Results

The following section first presents some descriptive market statistics and then evaluates the market design according to the previously described framework. We will show that that the EIX market is an active liquid market with low and improving forecast errors and that market generated forecasts are weak-form efficient.

5.1. Descriptive statistics

The following data includes the time span from the 30th October 2009 to the 15th of March 2010. In total 857 participants registered at the EIX market, of those 581 submitted at least one order. We have discarded all stocks (2) with less than 50 transactions. Altogether participants submitted 23,901 orders resulting in 11,708 executed transactions. In the respected time frame 17 stocks were paid out.

5.2. Market liquidity

The essential characteristic of a liquid market is that there are ready and willing buyers and sellers at all times. As the market was open 24/7 whereas financial markets operate only during office hours the trading activity was spread out over the day. Trading activity was fairly evenly distributed between 6 am and 1 am o'clock, with a slight peak at noon time. Hence, the typical security market liquidity measures were adapted to the longer trading day of the prediction markets we study. Realized spreads and price impacts for example are usually denoted in 15 or even 5 minute intervals. We calculated the realized spreads and price impacts for longer time intervals (3 to 24 hours).

Measure	Mean	Std. Dev.
Quoted Spread	135	319
Effective Spread	136	387
Quoted Spread at Trade	113	345
Realized Spread 3h	68	1136
Realized Spread 6h	64	1339
Realized Spread 12h	56	1351
Realized Spread 24h	49	1294
Price Impact 3h	63	1369
Price Impact 6h	67	1383
Price Impact 12h	75	1404
Price Impact 24h	83	1371
Trade Count/Stock	389	213
Trade Count/ Day	87	69

Table 3: Basic measures, all stocks combined

Table 3 presents the spread and price impact measures. The difference between quoted spread and quoted spread at trade (22 bps) shows that market participants observed the market and only actively triggered transactions by submitting market orders when spreads and thus implicit trading costs were low. Since quoted spreads at trade only measure the trading costs for the smallest of trade sizes, a more accurate measure of execution costs are given with the effective spreads. The realized spread represents the part of the effective spread that a liquidity supplier keeps as revenue. The price impact measures the information content of a trade. It reflects the permanent impact of a trade under the assumption that information impacts are permanent [18].
As Table 3 shows, the price impact increases if the measurement time is longer and the realized spread

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decreases. One can follow that the market needs some time to adapt to the information brought in by trades.

Indicator	Quoted Spread	Trade count	Variability (Std. Dev.)
Exports	217	2470	7.7
GDP	127	2414	1.9
Inflation	79	2443	0.7
Investments	202	1882	11.7
Unemployment	131	2490	1.7

Table 4: Average values per indicator

Table 4 displays the average spread measures for all stocks of the five different indicators. The last column gives the out-of-sample historic variability of each indicator. The variability can be interpreted as a risk measure for investors. Participants recognize the underlying risk as highly variable indicators such as Investments and Exports have high spreads and indicators with low historic variability exhibit low quoted spreads. Running an OLS regression (Quoted Spread = i+β * Variability) on a quote by quote basis the estimate (β) is 13.5, (statistical significant at the 1% level). An increase in the variability of 1 point increases the quoted spread of the representing stock by 13 basis points on average.

Turning to the probability of informed trading we find an average PIN of 0.353 and average α-values of 0.296. Compared to values from Easley et al. [10] we find that the probability that an information event occurs on a given day is equal (0.296 vs. 0.283). The risk a trader faces when trading is higher on the EIX prediction market than on NYSE (0.353 vs. 0.191).

5.3. Forecast errors

Table 5 reports the various error measures for three points of time before the official data release. As expected, the average forecast error is reduced over time as more public information becomes available. (t stands for the number of days before the data release)

	Market (t=10)	Market (t=5)	Market (t=1)	Bloomberg
MAE	1.22	1.32	1.08	1.42
MAPE	0.61	0.7	0.68	0.73
PMAD	0.45	0.51	0.46	-0.02
MSE	6.5	6.83	5.78	5.7
RMSE	1.55	2.6	2.4	2.4

Table 5: Market and Bloomberg forecast errors

In the last column the errors of the Bloomberg survey forecast are given. The time between the forecast and the data release varies as the Bloomberg forecast is made public on Fridays before the release. Nevertheless the prediction market (t = -10) forecast is in all cases before the Bloomberg forecast. The direct comparison of these two shows that they perform at least equally well. (There are no statistically significant differences).

5.4. Forecast efficiency

Table 6 presents the results of the previously presented OLS regression testing for weak-form forecast efficiency.

	α	β	γ
Revision	-0.001	0.001	-0.001
Std. Dev.	0.002	0.001	0.001
t-values	0.5	0.26	0.74

Table 6: Weak-form forecast efficiency

As the estimates (α,β,γ) are close to 0 one can interpret that the daily forecasts changes are not predictable. If one of the estimates would be significantly different from zero, the forecast revisions would not follow a random walk and one could assume a bias. Hence the weak form forecast efficiency is fulfilled which means that the forecast at a certain point of time contains all available information.

6. Conclusions

In this paper we provided a first analysis of forecasts generated from a new economic derivatives market. We first summarized findings from previous markets in this domain and detailed the known shortcomings of the so far used binary market designs. We proposed a radically different approach using a linear payout function. The theoretical improvements are threefold; first the number of traded stocks is reduced leading to higher liquidity in the traded stocks, secondly the 'partition-dependence' bias can been avoided and lastly information can be aggregated continuously and over longer time horizons.

Overall the market worked well. First we showed that the market is reasonably liquid in order to reflect the participants' information. Secondly the forecast error measures were reduced over time and the forecasts performed well in comparison to the 'Bloomberg'-survey forecasts. Thirdly forecasts generated by the market fulfill the weak-form forecast

efficiency implying that forecast changes were not predictable.

All three facts lead to the conclusion that a CDA market with linear payout functions works reasonably well and has inherent superior properties to markets with binary contracts. We hope our approach will positively impact the (prediction) market design community and forecast results will eventually influence economic policy making in Germany by providing continuous information about the state of the economy.

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